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High Density Salt and Pepper Impulse Noise Removal

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***Abstract*—In this paper, solution for very high density salt and pepper impulse noise is proposed. An algorithm is designed by considering the different parameters that influence the effect of noise reduction. The proposed algorithm contains two phases: Phase 1 detects the noisy pixels and Phase 2 replaces identified noisy pixels by non-noisy estimated values. Restored Mean Absolute Error (RMAE) is used to measure and compare the performance of the proposed algorithm. The algorithm is compared with several non-linear algorithms reported in the literature. Experimental results show that the proposed algorithm produces better results compared to the existing algorithms.**

***Index Terms*—Impulse Noise, Restoration, Image Enhancement, Image De-Noising, Adaptive Filters.**

I. Introduction

Digital image processing algorithms play a very vital role in all the fields of engineering and technology. Performance of algorithms basically relies on the quality of input image supplied to that algorithm. If the quality of input image is good then the quality of output is also good else we get low quality output. Efficiency of all image processing algorithms is directly proportional to the quality of input image. Hence, image quality enhancement or image de-noising techniques for images corrupted by various types of noises is one of the most important issues in digital image processing.

Impulse noise is one which may corrupt the images during their acquisition or transmission or storage etc. Several algorithms are proposed to remove impulse noise in the images. Some algorithms provide good results in low noise conditions and weak results in high noise conditions and vice versa. Further, such algorithms are not well-suited for real world applications to remove noise since they use prior knowledge of noise ratio that is not available in real world scenarios. Salt and Pepper Impulse Noise (SPIN) assumes a noise value of a minimumof 0 and a maximum of 255, as shown in equation (1).

$$X_{ij} = \begin{cases} 0 \text{ or } 255 & \text{Corrupted Pixel} \\ X_{ij} & \text{Non Corrupted Pixel} \end{cases} \quad (1)$$

The primary goal of this paper is to design efficient high density de-noising algorithms for images corrupted by SPIN, which produces consistent outputs in both low and high noise conditions without any assumption on image noise level in the algorithms so that these algorithms can be used in real-world applications without any modifications for different noise levels.

II. Methodology

In high noise conditions, the density of noisy pixels as well as the number of non-isolated noisy pixels increase. Hence noise signal transmission from one pixel to another pixel is more. To stop noise signal flow prior knowledge of noisy pixels are used. Hence,the proposed algorithm contains two phases: Phase1 detects the noisy pixels whilePhase 2 replaces noisy pixels by non-noisy estimated values.

our proposed salt & pepper impulse noise algorithm (PASPIN) is compared with Adaptive Median Filters (AMF)[1], Progressive Switching Median Filter (PSMF)[2], Tri-State Median Filter (TSMF)[3], Adaptive Fuzzy Switching Filter (AFSF)[4], A New Impulse Detector Based on Order Statistics Filter (NIND)[5], An Efficient Algorithm for the Removal of Impulse Noise from Corrupted Images (AEAFRIN)[6], A New Fast and Efficient Decision-Based Algorithm(DBA)[7], An Improved Adaptive Median Filter (IAMF)[8], Robust Statistics Based Algorithm (RSBA)[9], Decision Based Adaptive Median Filter (DBAF)[10], Image Restoration in Non-linear Filtering Domain Using MDB Approach (MDBF)[11], Detail Preserving Adaptive Filter (DPAF)[12] and A Universal Denoising Framework (UDF)[13].

A. Noise Detection

Algorithm 1is used to detect the noisy pixels present in the corrupted image C and the information about the corrupted pixels is stored in the binary image$N$.Scanning window W of size $2l+1$ is used to scan the corrupted image. Initial values of all pixels present in noise image are initialized to 0. To detect the corrupted pixels, the value of the variable is initialized to 1 and corrupted image is scanned by the scanning window. Center pixel of window is considered as test pixel. The test pixel is a non-corrupted pixel if the value of test pixel is greater than the minimum value of pixel present in the scanning window and less than the maximum value of the scanning window pixel. Otherwise,the test pixel is a corrupted pixel. If the test pixel is corrupted value 1 is stored in the corresponding position of noise image N. Calculate the number of 0's present in the noise image and store them in a variable. means the number of non-corrupted pixels present in the given input-corrupted image when window size . The algorithm is repeated if the value ofis greater than or equal to $C(l-1)$.

Algorithm 1

1. Take corrupted image C.

2. Initialize $l = 1$.

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3. Scan by window, initialize all binary noise image elements to 0 and consider the center pixel of scanning window of as test pixel .
4. Calculate and of scanning window pixels using the rest of the test pixel.
5. If and then is a corrupted pixel.
6. If is a corrupted pixel then set else set .
7. Calculate number of 0's present in and store in .
8. If then increment window size and repeat step 3 through step8 above.
9. Binary image is the final noise image.
10. Stop.

B. Restorationof Noisy Pixels

To calculate restoration value of noisy pixels, two main features such as direction and distance of neibouring pixels are used. This is based on the fact that not only the values of neibouring pixels contribute in the accurate calculation of replacement value but also their direction and distance from central pixel play a vital role in replacement value calculation.

1. *Direction-Based Selection*

To calculate the replacement value of a noisy pixel, odd size window of length $Wl = 2k + 1$ is used. Selected window is divided into eight equal regions R1 to R8 in eight directions. Center pixel of the window (0, 0) is considered as test pixel. Initial value of *k* is 1 and value of *k* increases until all the regions of window contain at least one uncorrupted or non-noisy pixel. Maximum value of *k* is 25. Figure1 shows the arrangement of pixels in the window regions.

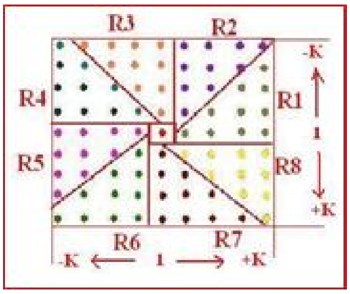

Figure1. Internal Distribution of Window Pixels

2. *Distance-Based Selection*

Based on distance from central pixel, eight neibouring nearest non-corrupted pixels P1 to P8 one each from eight regions are selected. Figure2 shows the pixels of eight regions present in the window. A black pixel indicates corrupted pixel and a white indicates non-corrupted pixel. Equation (2) shows the distance calculation.

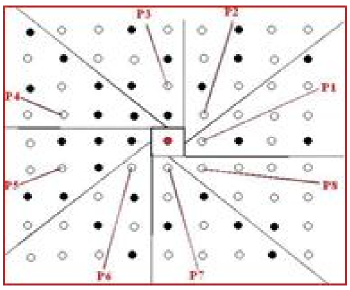

Figure 2. Selected Pixels from Eight Regions of Window

$$Distance\ D(m,n) = \sqrt{m^2 + n^2} \quad (2)$$

3. *Weight Calculation*

Both the value and the distance of selected neibouring pixels play vital role in the calculation of replacement value. We combine both value and distance of pixels D1 through D8 to convert into weights W1 through W8. Weight valuesvary from 255 to 1. Maximum value present in the distance vector Di is considered as Wmin and minimum value present in the distant vector Di is considered as Wmax. Nearer pixels are assigned more weights compared to fatherones. Nearer pixel weights are assigned 255 and farther distance pixel weights are assigned 1 because nearer pixels contribute more compared to the farther distance pixels in calculation of replacement value, as shown in equation (3).

$$W_i = 1 + \left(\frac{(D_i - W_{min}) \times 255}{W_{max} - W_{min}}\right) \quad (3)$$

4. *Replacement Value*

To calculate the replacement value of center pixel equation (7) is used. Nearest non-corrupted pixel P_i values are taken from each region from R1 to R8. Replacement value is calculated by taking weighted mean of all selected pixel values, as shown in equation (4).

$$Replacement\_Value = \frac{\sum_{i=1}^{8} W_i \times D_i}{\sum_{i=1}^{8} W_i} \quad (4)$$

To restore corrupted image, corrupted image is scanned from top to bottom, row by row using odd sized window Wl. In each scan, check the status of central pixel (0,0). If it is a corrupted pixel then replace its value by its replacement value. To scan window of size 2k+1, variables i and j are used. Minimumand maximum values of i and j are –k and +k.

III. Performance Measurements

To evaluate the performance of the impulse noise algorithms the performance measure RMAE (Restored Mean Absolute Error), as shown in equation (5), is used. RMAE is measured using unit decibel (db). RMAE is the amount of Mean Absolute Error (MAE) recovered by an algorithm. Mean absolute error (MAE) gives the difference between the given two input images, as shown in equation (6). Low value of MAE indicates more similarity between the given images and vice versa. MAE value changes from 0 to 255. Zero value of MAE indicates that both images look exactly the same.As MAE value increase towards 255 similarities between the images decreases.RMAE is calculated as the percentage ratio of the difference of corrupted image mean absolute error and restored image mean absolute error and corrupted image mean absolute error, as shown in equation (6).RMAE is the percentage amount of noise restored by an algorithm. Maximum value of RMAE is 100, indicating that both original and restored image are exactly the same meaning the restoration is 100%; that is,the algorithm has successfully restored all corrupted pixels. Sometimes,the algorithm returnsa negative value of RMAE indicating that the algorithm is increasing

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the noise ratio instead of restoring the image. RMAE value is 100% if the restored image MAE is the same as the corrupted image MAE; all corrupted pixels are restored in this case. For good restoration algorithms, restored image MAE is less than the corrupted image MAE else we get negative RMAE value indicating bad restoration. MAE value increases and RMAE decreases with increase in noise ratio.

$$RMAE = 1 - \frac{(MAE\ of\ Corrupted\ Image - MAE\ of\ Restored\ Image)}{MAE\ of\ Corrupted\ Image} \quad (5)$$

$$MAE = \frac{\sum_i^M \sum_j^N (x_{ij} - R_{ij})}{(M \times N)} \quad (6)$$

Where

X-Original Image. R-Restored Image

M X N - Size Of Image. MAE-Mean Absolute Error.

RMAE-Restored Mean Absolute Error.

IV. Simulation And Results

Different natural images are used to evaluate the performance of the proposed algorithm using theperformance measure RMAE. Figures2 and 4 show the restoration results of the proposed algorithm of the imagesin Figures 1 and 3 for different levels of noise ratio. Visibility of the output of 90% noisy image clearly shows that efficiency of the proposed algorithm is very high. Tables 1 and 2 and Figures6 and 8 show the restoration results of different filters and visibility of outputs of images in Figures 5 and 7. This again clearly shows that the efficiency of the proposed algorithm is high compared to other algorithms. Graphical analyses of results are shown in Figures9 and 10.

Figure 1. Original Image 1 (280X280)

10% NOISE RATIO

30% NOISE RATIO

RESTORED IMAGE OF 10% NOISE RATIO RMAE= 98.23

RESTORED IMAGE OF 30% NOISE RATIO RMAE= 97.94

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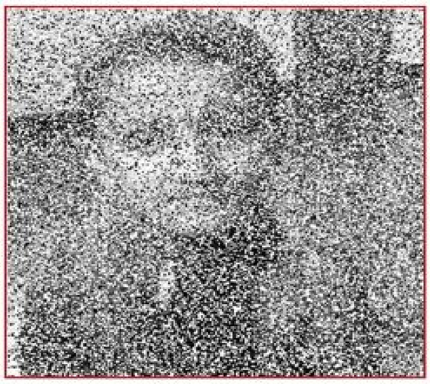
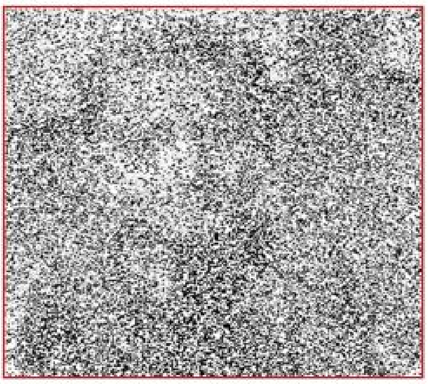
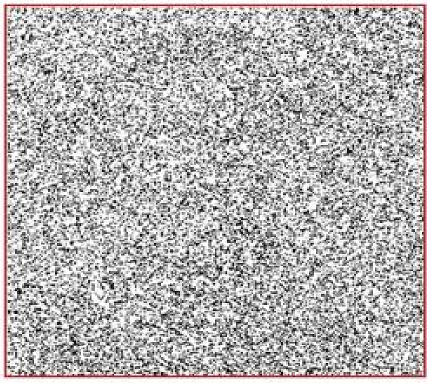


50% NOISE RATIO



70% NOISE RATIO



90% NOISE RATIO

RESTORED IMAGE OF 50% NOISE RATIO RMAE= 97.60

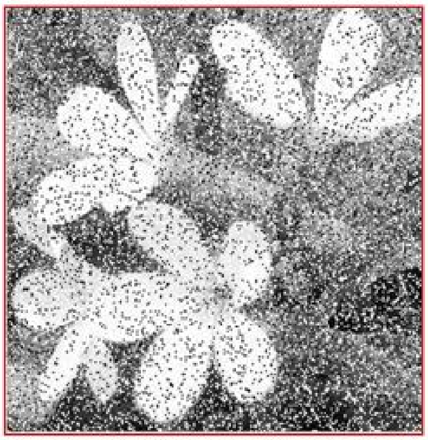
RESTORED IMAGE OF 70% NOISE RATIO RMAE= 97.09

RESTORED IMAGE OF 90% NOISE RATIO RMAE= 95.64

Figure 2. Restoration Results Of Images-1 Upto 90% Of Noise Ratio

Figure 3. Original Image 2 (250X250)

10% NOISE RATIO



30% NOISE RATIO

RESTORED IMAGE OF 10% NOISE RATIO RMAE= 95.72

RESTORED IMAGE OF 30% NOISE RATIO RMAE= 95.63

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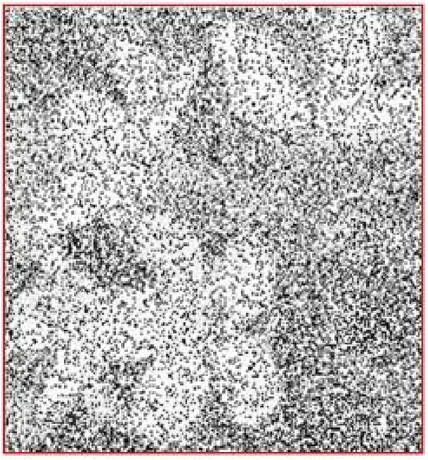
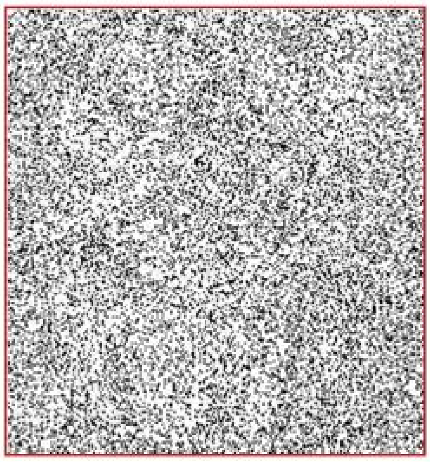
50% NOISE RATIO



70% NOISE RATIO



90% NOISE RATIO

RESTORED IMAGE OF 50% NOISE RATIO RMAE= 95.13

RESTORED IMAGE OF 70% NOISE RATIO RMAE= 93.98

RESTORED IMAGE OF 90% NOISE RATIO RMAE= 90.78

Figure 4.Restoration Results Of Images-2 Upto 90% Of Noise Ratio

TABLE I. RMAE VALUES FOR SPIN IMAGE-3(230X230)

NOISE RATIO ? / FILTERS ?	10	20	30	40	50	60	70	80	90
AMF	97.13	97.49	97.3	96.77	95.82	86.95	60.6	26.77	9.59
PSMF	97.4	97.5	97.01	92.28	73.81	24.34	-1.48	-14.77	-15.83
TSMF	66.15	82.98	87.5	85.21	71.02	39.68	5.18	-15.42	-18.3
AFSF	96.44	96.51	95.99	93.98	90.32	84.35	74.08	61.31	45.85
NIND	98.43	98.04	96.7	87.62	57.91	16.89	-20.59	-29.05	-22.19
AEAFRIN	93.27	91.02	82.52	66.16	46.35	27.46	9.03	-5.09	-10.53
DBA	98.38	98.13	97.78	97.22	96.36	94.94	91.43	78.88	27.1
IAMF	97.27	96.96	96.3	92.78	50.51	11.58	-8.07	-26.41	-22.82
RSBA	97.39	97.7	97.32	96.91	96	93.49	61.16	24.97	6.4
DBAF	96.81	92.62	79.63	59.36	34.82	8.25	-10.39	-19.02	-18.16
MDBF	96.84	94.99	89.37	78.3	60.97	43.69	25.34	10.54	-2.02
DPAF	97.19	97.51	97.26	96.79	95.45	89.24	58.79	27.73	9.08
UDF	95.34	96.47	96.62	96.39	95.86	92.1	69.13	23.28	-12.71
PASPIN	98.84	98.72	98.62	98.53	98.38	98.24	98.09	97.7	96.92

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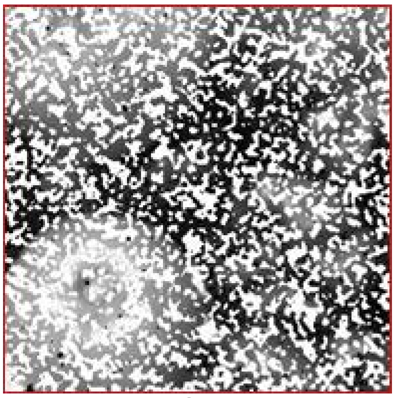
Table II. Rmae Values For Spin Image-4 (300x300)

NOISE RATIO ? / FILTERS ?	10	20	30	40	50	60	70	80	90
AMF	90.31	92.66	93.19	92.58	91.63	85.14	55.23	24.73	8.6
PSMF	75.48	85.44	87.79	84.09	66.39	18.37	-5.1	-17.34	-19.03
TSMF	35.43	66.63	76.2	76.07	62.41	32.35	0.44	-20.29	-22.94
AFSF	78.32	86.62	88.86	88.41	85.46	79.8	70.01	57.57	42.87
NIND	79.9	87.77	88.37	79.01	55.65	12.64	-21.25	-32.19	-26.28
AEAFRIN	74.52	79.76	74	60.57	41.02	20.99	3.66	-9.2	-14.15
DBA	95.86	95.37	94.65	93.77	92.77	90.42	86.7	72	8.19
IAMF	76.74	84.77	85.38	79.73	42.97	10.01	-11.79	-28.85	-27.49
RSBA	90.41	92.64	92.58	92.12	90.76	88.19	58.9	22.07	5.64
DBAF	78.07	81.08	71.16	51.24	27.11	2.61	-15.47	-24.38	-22.25
MDBF	89.71	90.81	85.09	73.99	58.16	40.33	21.57	6.34	-5.25
DPAF	89.83	92.65	93.05	92.39	91.26	84.02	54.25	24.92	8.18
UDF	56.63	77	83.85	86.91	88.49	87.12	74.82	32.87	-16.25
PASPIN	96.3	96.22	95.94	95.69	95.43	95.17	94.65	93.95	92.7

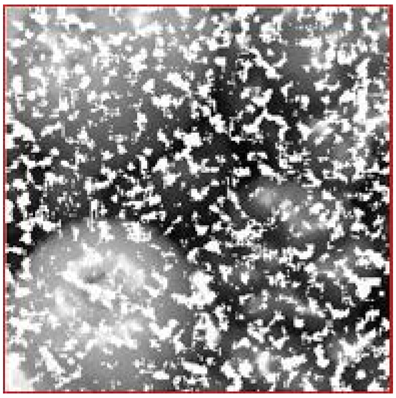
Figure 5. Original Image 3 (230X230)

PASPIN

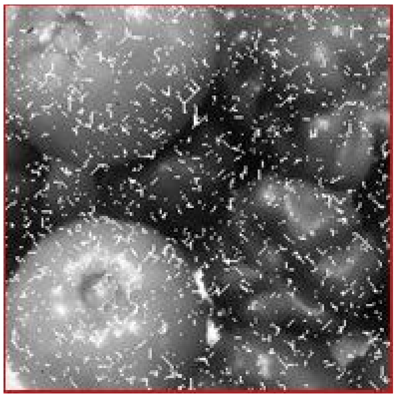
AMF



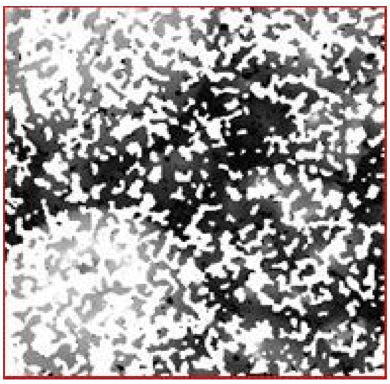
PSMF



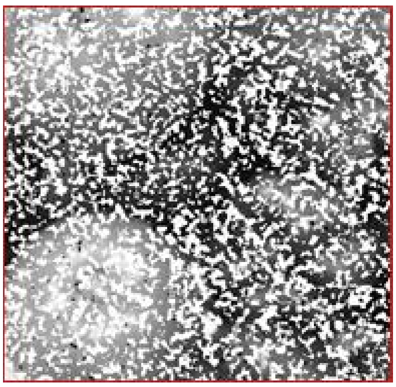
TSMF



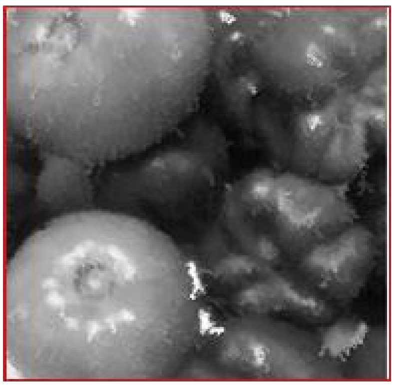
AFSF



NIND



AEAFRIN



DBA

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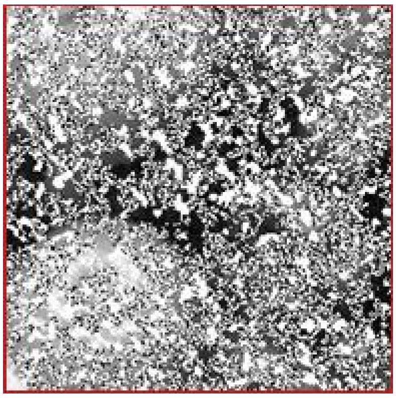
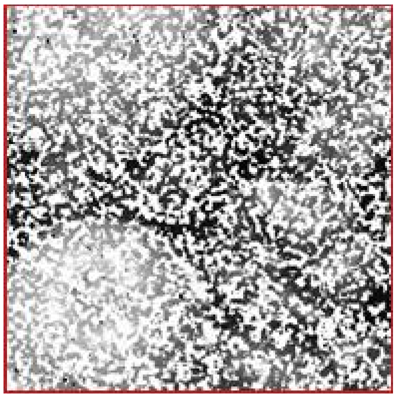
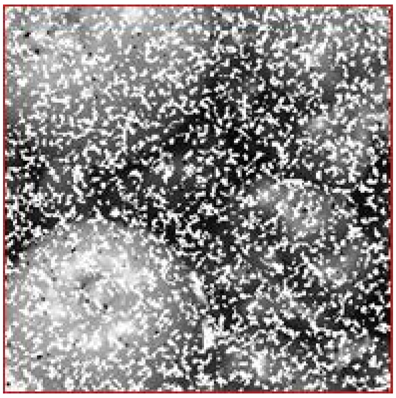


IAMF

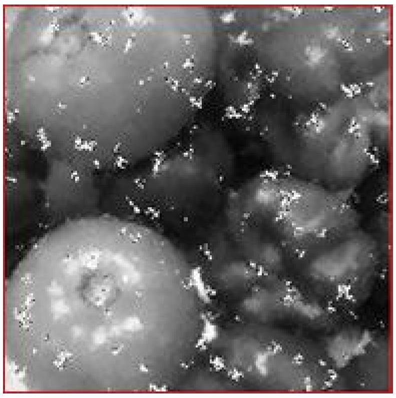
RSBA



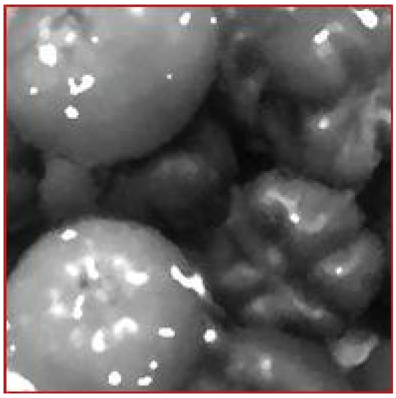
DBAF



MDBF



DPAF

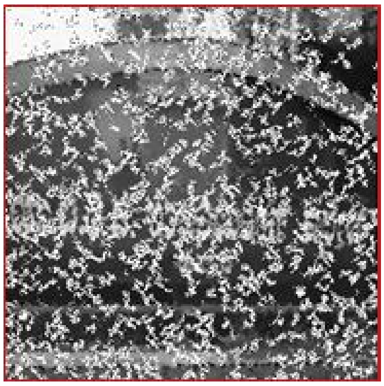


UDF

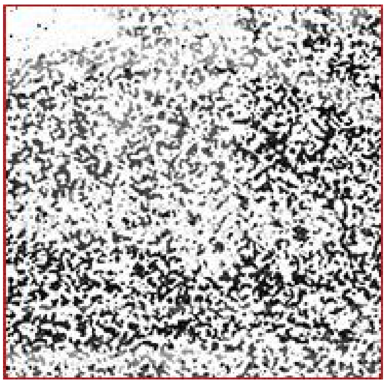
Figure 6.Results Of Filters For Image-3 (230x230) With 60% Spin

Figure 7. Original Image 4

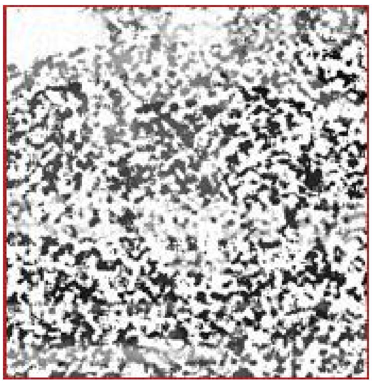
PASPIN



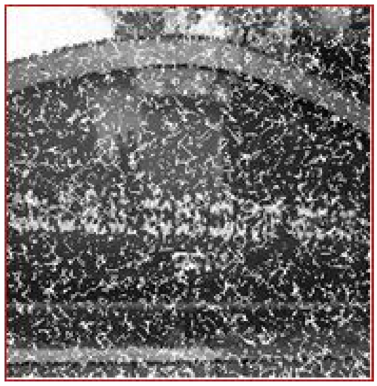
AMF



PSMF



TSMF



AFSF

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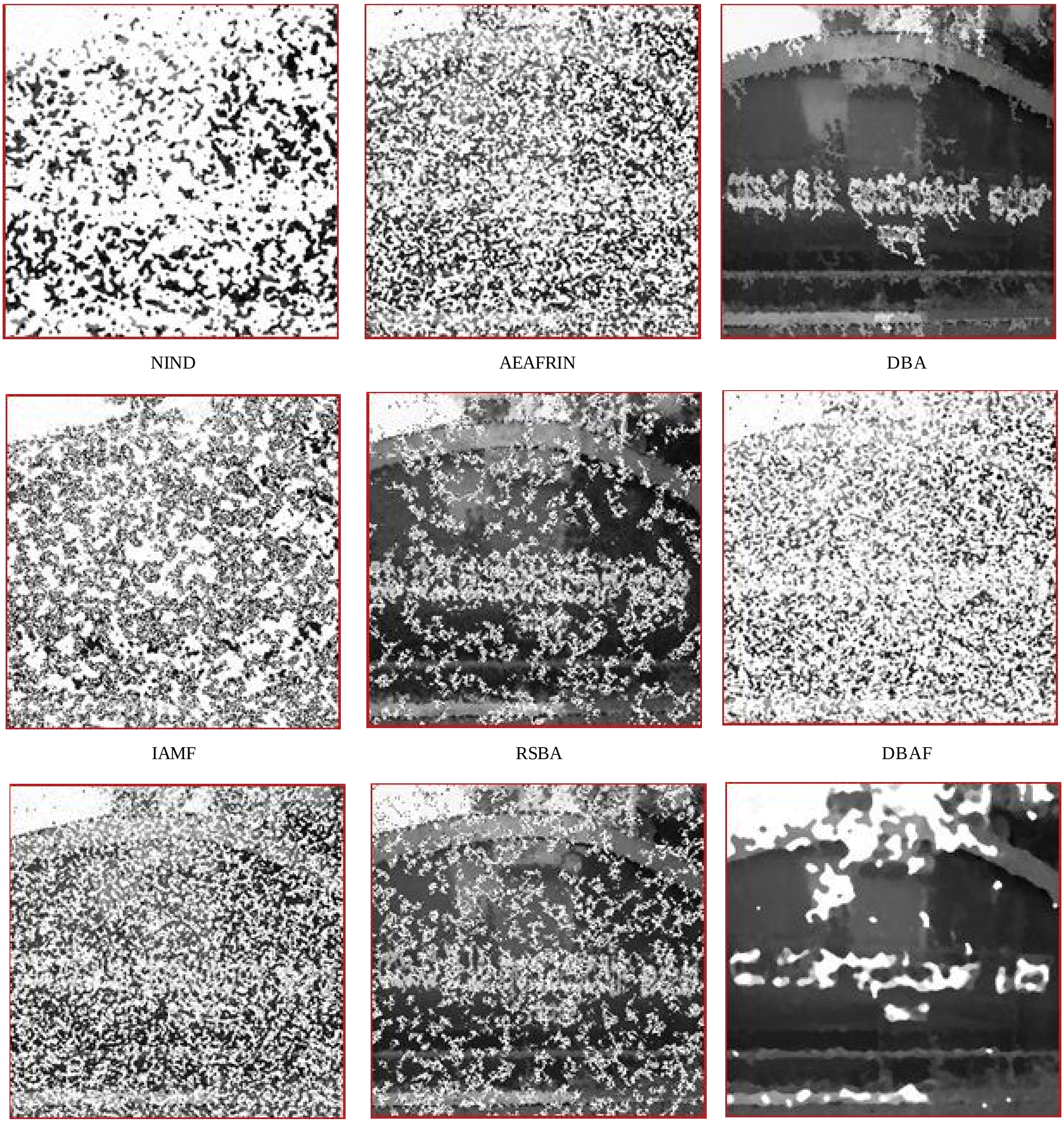

Figure 8..Results Of Filters For Image-4 (300x300) With 70% Spin

V. ConclusionS

In this paper, an efficient two phase algorithm to remove salt and pepper impulse noise from gray scale image is proposed. The proposed algorithm controls the flow of noise signal and produces consistent and very high quality output. Experimental results shows that the efficiency of the algorithm is very high compared to other algorithms. The proposed algorithm works well in both the low and the high noise ratio up to 98%. This algorithm is a promising solution for impulse noise reduction as it maintains consistency in performance. Study of the suitability and performance of the proposed algorithm for other types of noise and images is part of our future work.

References

[1] H. Hwang and R. A. Haddad “Adaptive Median Filters: New Algorithms and Results”IEEE Transactions on Image Processing, Vol. 4, No. 4, April 1995,pp 499-502.

[2] Zhou Wang and David Zhang “Progressive Switching Median Filter for the Removal of Impulse Noise from Highly Corrupted Images”IEEE Transactions on Circuits and Systems—II: Analog and Digital Signal Processing, Vol. 46, No. 1, January 1999,pp 78-80.

[3] Tao Chen, Kai-Kuang Ma,Li-Hui Chen “TriSstate Median Filter for Image Denoising”IEEE Transactions on Image Processing, Vol. 8, No. 12, December 1999,pp 1834-1838.

DOI: 01.IJSIP.5.1.8

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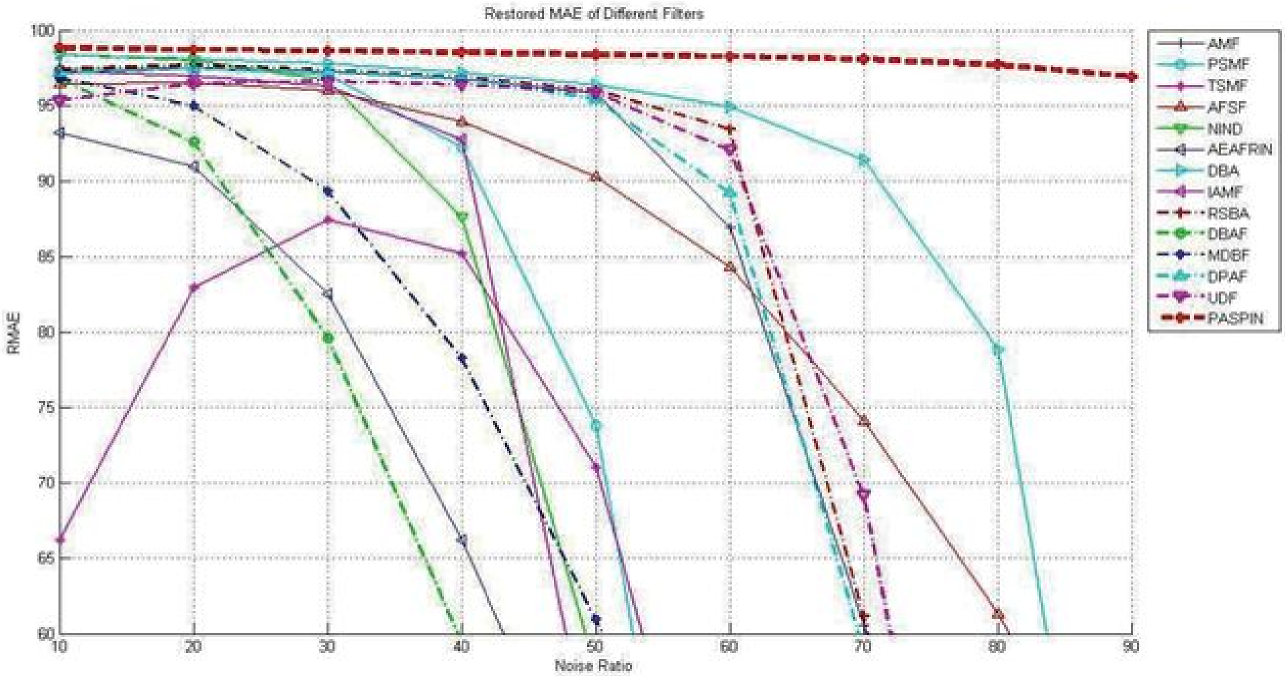

Figure 9.Rmae Of Filters For The Image-3 (230x230)

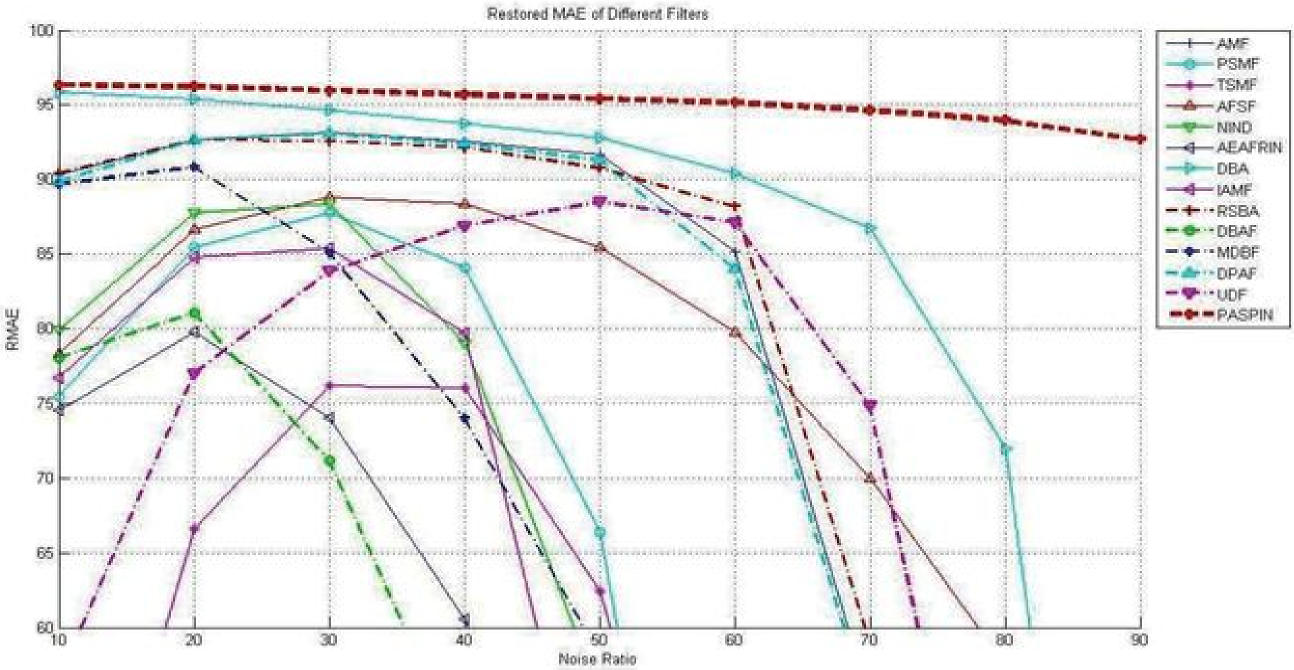

Figure 10. Rmae Of Filters For The Image-4 (300x300) With Spin

[4] Haixiang Xu, Guangxi Zhu, Haoyu Peng, Desheng Wang "Adaptive Fuzzy Switching Filter for Images Corrupted by Impulse noise" Pattern Recognition Letters 25 (2004) pp 1657–1663.

[5] Wenbin Luo"A New Impulse Detector Based on Order Statistics" Intl. J. Electronincs Communication (aeü) 60 (2006) pp 462–466.

[6] Wenbin Luo "An Efficient Algorithm for the Removal of Impulse Noise from Corrupted Images"Intl. J. Electron. Commun. (aeü) 61 (2007) pp 551 – 555.

[7] K. S. Srinivasan,D. Ebenezer"A New Fast and Efficient Decision-Based Algorithm for Removal of High-Density Impulse Noises"IEEESignal Processing Letters, Vol. 14, No. 3, March 2007,pp 189-192.

[8] Mamta Juneja, Rajni Mohana"An Improved Adaptive Median Filtering Method for Impulse Noise Detection"International Journal of Recent Trends in Engineering, Vol. 1, No. 1, May 2009,pp 274-278.

[9] V.R.Vijaykumar, P.T.Vanathi, P.Kanagasabapathy, D.Ebenezer "Robust Statistics Based Algorithm to Remove Salt and Pepper Noise in Images"International Journal of Information and Communication Engineering 5:3 2009,pp 164-173.

[10] V.R.Vijaykumar,Jothibasu "Decision Based Adaptive Median Filter to Remove Blotches, Scratches, Streaks, Stripes and

Impulse Noise in Image" Proceedings of 2010 IEEE 17th International Conference on Image Processing,September 26-29, 2010, Hong Kong,pp 117-120.

[11] S. K. Satpathy, S. Panda, K. K. Nagwanshi,C. Ardil "Image Restoration in Non-linear Filtering Domain Using MDB Approach" International Journal of Information and Communication Engineering 6:1 2010,pp 45-49.

[12] Krishna Kant Singh, Akansha Mehrotra, Kirat Pal, M.J.Nigam "A n8(p) Detail Preserving Adaptive Filter for Impulse Noise Removal" 2011 International Conference on Image Information Processing (ICIIP 2011).

[13] Bo Xiong,D.Zhouping Yin "A Universal Denoising Framework with a New Impulse Detector and Non-local Means" IEEE Transactions on Image Processing, Vol. 21, No. 4, April 2012,pp 1663-1675.

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